PRACTICE SPOTLIGHT

Algorithmic human resource management: A brief introduction and managerial toolkit

Novika Grasiaswaty

NOVIKA GRASIASWATY

Adam Smith Business School, University of Glasgow, Scotland
Industrial and Organizational Psychology, Universitas YARSI, Indonesia

novika.kamal@glasgow.ac.uk

About the author

Novika Grasiaswaty is a doctoral researcher at the Adam Smith Business School, University of Glasgow. With a background in industrial and organizational psychology, Novika's work explores how platform workers respond to automation systems. She is currently developing a scale to measure platform worker resistance to algorithmic management. Following scale development study, Novika's PhD will examine the dynamics between algorithmic management and platform worker resistance behaviour through the lens of self-determination theory.

Acknowledgments

The preparation of this paper was supported by the Indonesia Endowment Fund for Education (LPDP), Ministry of Finance of the Republic of Indonesia. The author is also grateful to YARSI University for its academic and institutional support throughout the writing process. Special thanks are extended to Dr. Belgin Okay-Somerville for their valuable feedback on the initial draft.

Abstract

As algorithmic systems increasingly shape workplace dynamics, human resource management (HRM) is undergoing a profound transformation. Algorithmic HRM – defined as the use of software algorithms to automate or augment HR-related decisions – offers potential gains in efficiency and objectivity across the different HRM processes. However, its implementation also raises critical concerns about fairness, transparency, worker autonomy and trust. This paper explores the defining features of algorithmic HRM, examines its implications for employee experiences, and analyses emerging risks. It concludes with a managerial toolkit for responsible algorithmic HRM, outlining reflective questions and strategies that HR professionals can use to align algorithmic practices with ethical standards, employee well-being, and organizational integrity.

Keywords: Algorithmic Human Resource Management, responsible AI, trust-based algorithmic implementation

Introduction

In 2005, "I, Robot", a film set in the year 2035, captured the attention of my younger self with its portrayal of a future where humans live alongside autonomous robots. The movie featured Will Smith as Detective Del Spooner and depicted a world where robots were seamlessly integrated into everyday life, handling everything from household chores to more complicated tasks. Fast forward to today, it is remarkable to see the parallels between the film's vision and our everyday reality. We have witnessed the emergence of smart home devices, autonomous vehicles, and other automatic systems echoing the film's portrayal of highly intelligent and independent robots. Technology has been shaping every aspect of our working lives through digitalisation. This shift is also changing how we work, communicate, and connect with employers, especially reshaping employee management – a field traditionally seen as minimally data driven. As advancements in technology continue to transform the workplace, human resource management (HRM) is undergoing a substantial shift.

Significant HRM technology trends have emerged, including the expanded use of artificial intelligence (AI) and algorithms in managing people in the workplace, now commonly referred to as algorithmic human resource management. First coined by Meijerink et al. (2021), algorithmic HRM refers to the "use of software algorithm that operate on the basis of digital data to augment HR-related decisions and/or to automate HRM activities" (p. 2547) and reflects a growing trend in contemporary people management. For instance, 81% of HR professionals are positive about incorporating AI into HRM operations (Soliman, 2025). The AI market for HR was estimated to be worth $3.25 billion in 2023 (Grand Review Research, 2025) and is expected to grow to $17.61 billion by 2027 (Dube, 2025). Unlike previous technological applications in HRM that primarily served as tools to assist human decision-makers, algorithmic HRM marks a significant breakthrough. Algorithmic HRM not only supports but also actively participates in the decision-making process, representing a substantial evolution in the field. In this rapidly advancing landscape, it is crucial for organizations to understand how employees experience and respond to technological advancements in HRM (Bondarouk & Brewster, 2016; Rubel et al., 2017). This paper introduces the concept of algorithmic human resource management, a novel intersection of technology and human resource management, and offers a managerial toolkit for managing people in the workplace through algorithmic HRM.

Defining features of algorithmic human resource management

Algorithmic HRM systems are designed to enhance and sometimes completely automate decision-making process related to human resource management (Duggan et al., 2020). This data-driven approach allows for more informed and accurate decision-making in many areas of people management, such as talent management, performance evaluation, and workforce planning. By leveraging algorithms and machine learning, algorithmic HRM systems can analyse massive amounts of data and identify patterns and trends that may not be easily recognizable.

The distinctive feature that sets algorithmic HRM apart from earlier technologies lies in its ability to independently make judgments and decisions based on the input data. This capability marks a significant advancement over traditional systems, which typically required more direct human intervention and oversight. Workers, particularly those who work on digital labour platforms, such as Uber, Upwork and Deliveroo, can now be screened, hired, trained, disciplined, rewarded and even fired by algorithms (Meijerink & Keegan, 2019; Möhlmann & Zalmanson, 2017; Parent-Rocheleau et al., 2024). With the adoption of algorithmic HRM, companies are shifting control and evaluation functions, previously managed by line managers, to systems and machines. This transition allows for more streamlined and automated processes in workforce management. In other words, algorithmic HRM becomes an invisible manager in the contemporary world of work (Gandini, 2018).

AI-based systems are often user-friendly and therefore easy-to-use. The automated nature of algorithmic HRM processes indeed simplifies various HR tasks, providing a seamless experience for both the employer and employees. This comfort factor contributes to increased user adoption and satisfaction within the system.

Undoubtedly, algorithmic HRM represents significant innovation in strategic HRM, which aims to ensure that the workforce is equipped with the right capabilities for achieving organizational goals. Accordingly, efficiency gain (Weiskopf & Hansen, 2023; Wesche & Handke, 2023) is the most visible and direct advantage of algorithmic HRM: Algorithmic HRM systems enable more rapid and consistent decision-making, reducing the time and resources traditionally required for human resource tasks. For instance, recruiters in L'Oreal report companies in the beauty and cosmetics industry receive approximately 5 million applications annually and algorithms help streamline screening and selection decisions and increase efficiency of decisions (Charlier & Kloppenburg, 2017).

Crucially, it is argued that through algorithmic HRM companies can achieve more objective and consistent assessments of candidate and employee performance, thereby minimising potential biases inherent in human decision-making (Davenport, 2014; Scholz, 2019). However, research shows us that algorithmic decision making is only as good as the data that is it is trained on. Algorithmic decision making may therefore be reinforcing existing biases in decision making. Moreover, by removing human involvement in decision making, algorithmic HRM may have dehumanising effects, with implications for human agency at work and job quality. We next review these unintended consequences of algorithmic HRM.

Fairness of algorithmic HRM systems

Fairness and objectivity are crucial in fostering equitable and effective people management practices, ensuring HR decisions are based on relevant metrics and criteria. Despite efficiency gains, algorithmic management raises serious concerns regarding fairness of algorithmic management practices, as well as its impact on employee experience of work. Although it makes common-sense to believe that algorithms are more 'bias-free' than humans' subjective decision making, issues of bias and discrimination have been reported in scenarios where algorithmic HRM serves as the decision-maker (Lavanchy et al., 2023). This was most certainly the case for Amazon's AI recruiting tool, which, mirroring the tech industry's male skew, learnt to prefer male candidates over female candidates (Dastin, 2022).

Similarly, it was shown that Facebook's job ad targeting by gender encourages discrimination and perpetuates gender imbalances in job visibility. An investigation by Duffy and Dotto (2023) shows that in France, Facebook's ad manager platform data showed that ads for preschool teacher and psychologist jobs were predominantly displayed to women. Conversely, only 25% of those seeing pilot job ads and a mere 6% of mechanic job ad viewers were women. In a similar trend in the Netherlands, 85% of those who saw teacher job ads and 96% of receptionist job ad viewers were women, while only 4% of mechanic job ad viewers were female. However, some job adverts, like those for package delivery positions, had a less pronounced gender bias, with 38% of the audience being women (Duffy & Dotto, 2023). These patterns align with findings in the United Kingdom, where women were more frequently targeted with ads for nursery teacher and psychologist roles, while men predominantly saw pilot and mechanic job ads (Kavakeb, 2023). This trend reflects a broader issue where modern technologies inadvertently reinforce past discriminatory patterns, hindering progress in correcting these biases. Accordingly, there are currently heated debates around regulation (Adams-Prassl et al., 2023) and ethics of Algorithmic HRM (Hunkenschroer & Luetge, 2022; Loveday, 2024).

Personal agency in algorithmic HRM

Algorithmic HRM, like any other system, needs input to analyse and make decisions. It is argued that by quantifying workers' lived experiences, algorithmic HRM systems may have dehumanising effects. For instance, workers' interactions with customers and/or their daily movements are all codified into data on digital work platforms, such as Deliveroo (Popan, 2024). This phenomenon, rooted in the pervasive use of algorithmic systems and big data analytics, reduces complex human behaviours, skills and interactions to mere data points and numbers. Consequently, workers tend to be seen more as interchangeable parts of a system rather than as unique individuals with distinct talents, feelings and capabilities (Lamers et al., 2022). Accordingly, concerns have been raised regarding workers' personal agency in algorithmic HRM systems.

According to labour process theory managers will continually seek ways to establish and maintain control over workers to increase efficiency gains (Braverman, 1998). A labour process theory perspective indeed informs the majority of research on algorithmic management and its impact on workers' agency. It is argued that algorithmic HRM, through increased managerial surveillance and control, may significantly limit workers' job autonomy and control (Duggan et al., 2020; Kellogg et al., 2020). Such restraining effect on worker autonomy and control is particularly problematic in digital work platforms (such as Uber and Deliveroo) that connect workers with clients, and thus may not necessarily be classified as 'employers' in the eyes of employment law. Digital work platforms rely heavily on algorithmic control systems to regulate exchange of services between workers and clients. Platform workers may not be able to access employee legal protections, such as the national minimum wage, working time regulations, unfair dismissal or collective employee rights (Prassl & Risak, 2017). While some argue that platform work functions as a social equalizer, opening opportunities for additional earnings for those who need it most (Hoang et al., 2020) and praised for the flexibility they offer workers in choosing work (Gondim et al., 2024), empirical evidence shows that platform work may provide varying degrees of autonomy and control over working time and work organization (including goal setting) and financial security (e.g., by the hour, per task or based on the outcome of work). At the most extreme, management of workers on digital work platforms has been described as flexible exploitation, flexploitation, particularly when digital platforms rely heavily on migrant workers or refugees who are in more vulnerable positions in labour markets with less bargaining power (Popan, 2024).

Job quality and employee outcomes associated with algorithmic HRM

The impact of narrowly defined and heavily controlled jobs on workers is well known. Similarly, there is emerging research demonstrating how algorithmic management and associated prolonged loss of worker autonomy, characterized by the continuous repetition of discrete tasks under strict instructions, can prevent workers from practicing, developing competences and acquiring knowledge in their jobs (Baiocco et al., 2022). This phenomenon can lead to de-skilling of the workforce.

The emphasis on quantitative metrics can create a work culture where the value of an employee is solely determined by their data output. This not only diminishes the sense of individuality among workers but also fosters an environment where the qualitative aspects of work – such as employee well-being, job satisfaction and team dynamics – are undervalued or ignored. The impersonal nature of this approach may lead to a workforce that feels alienated and undervalued, where the human element of work is overshadowed by the pursuit of data-driven results. As such, the challenge lies in finding a balance between leveraging the benefits of data and algorithms while maintaining a work culture that respects and nurtures the human qualities of its workforce. In fact, detrimental effects of pervasive monitoring and surveillance in the workplace have been reported (Baiocco et.al., 2022). Such practices can hinder workers from making autonomous decisions, either to avoid punitive measures such as dismissal, or to pursue rewards. This loss of autonomy is identified as a significant job quality issue, as it restricts individual discretion, potentially leading to alienation, detachment from one's job, and decreased job satisfaction. It can also contribute to emotional exhaustion.

There is also the potential for social isolation or alienation, where reliance on algorithmic systems might limit interpersonal interactions in the workplace (Frey, 2020). It is crucial to understand how these systems might impact interpersonal interactions. Algorithmic systems can create environments where workers are more focused on data-driven tasks, reducing opportunities for human interaction and collaboration. This shift can lead to feelings of isolation and alienation, as employees may find themselves disconnected from their colleagues and the broader organizational culture.

Empirical evidence on worker reactions to algorithmic HRM is a fast-emerging field within strategic HRM literature. Although much of the work on algorithmic management assumes that workers are passive recipients of these practices guided by algorithms, there is evidence that workers may actively manipulate and leverage algorithmic management (Bucher et al., 2021; Cameron & Rahman, 2022; Popan, 2024). Algorithmic resistance presents further challenges for organizations to address (Cram et al., 2022). Resistance to algorithmic systems can manifest in two forms: firstly, resistance to the implementation of such technologies, and secondly, resistance through the use of these algorithmic systems themselves (Bonini & Treré, 2024). Both types of resistance behaviour could lead to unintended consequences for organizations. Algorithmic resistance behaviour can manifest in subtle acts such as deliberately providing false or misleading data to the algorithmic control system – for instance, encouraging customers to give inflated ratings or attempting to 'game' the system to improve performance scores. Within the context of digital labour platforms, such resistance is frequently discussed and shared in informal online spaces such as Reddit and Facebook, where workers exchange strategies for navigating or subverting algorithmic control. For instance, the Reddit post in Figure 1 describes how an UberEats worker resists algorithmic control by declining orders for delivery and urging fellow UberEats workers to do similar for their voices to be heard.

Figure 1. Sample algorithmic resistance behaviour on an informal forum

The role of HR professionals in the algorithmic HRM context

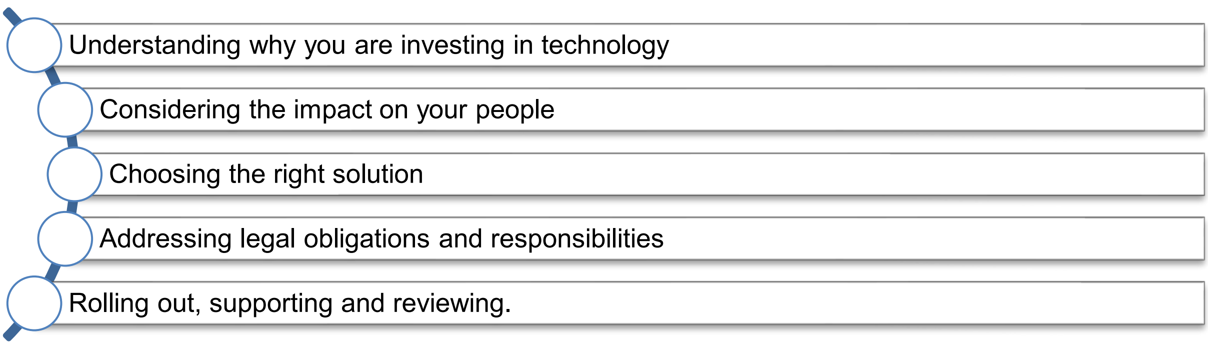
Biases inherent in self-learning algorithms, as well as system transparency concerning how key employment-related decisions are made can impact workers' perceptions of fairness and trust in algorithmic management systems. Transformation of employee management using algorithmic management tools have implications for the skills and capabilities of HR professionals and the policies and practices they develop for managing people in the workplace. HR professionals must ensure that algorithmic systems are aligned with the organization's ethical standards and strategic goals – this is the foundation of responsible algorithmic HRM. At the same time, they must foster an environment of trust, where employees are fully informed and reassured about how these technologies influence their work and career trajectories – referred to here as trust-building algorithmic HRM.

Responsible algorithmic HRM

Algorithmic decision-making blurs responsibility for outcomes because algorithms are not subject to laws and regulations human managers are (Association for Computing Machinery [ACM], 2017; Breidbach, 2024). Nevertheless, algorithmic HRM may result in significant consequences for workers, such as, as discussed above, bias and discrimination, loss of agency and unfair treatment in the workplace. In the absence of regulations that govern algorithmic management systems, how can HR professionals ensure that algorithmic decision-making is used responsibly in their organizations, i.e., in a way that minimises its adverse consequences?

Accordingly, the Chartered Institute of Personnel and Development (CIPD, 2024) suggests the following checklist for responsible investment in technology, presented in Figure 2. In fact, "use AI only if it makes sense, otherwise avoid!" is a suggestion reported by senior managers when asked how to avoid algorithmic bias (CIPD, 2023).

Figure 2. Responsible investment in technology



Source: CIPD (2024)

Several tools and frameworks now exist that illustrate how organizations can use AI responsibly in management of work and workers. Broader frameworks (e.g., ACM, 2017) consider responsible use of AI in general and highlight the importance of:

- Awareness of biases and their consequences to individuals and the society.
- Questioning and redressing negative consequences of decisions made by algorithmic systems.
- Accountability for decisions made by algorithms to be on the organizations.
- Explanation of the procedures that use algorithmic decision making and the specific decisions taken by algorithms.
- Data sources used in training algorithms should be transparent, and open to scrutiny of any biases.
- Auditability of the data, algorithms and decisions, is particularly important in the face of adverse consequences.
- Validation and testing to ensure that algorithmic models are based on rigorous methods.

Crucially, responsible and accountable algorithmic decision making systems have been shown to be critical for ensuring procedural fairness, associated with fair treatment of workers (Meijer & Grimmelikhuijsen, 2020). We next consider how algorithmic HRM can foster an environment of trust.

Trust-building algorithmic HRM

Trust refers to one's "willingness to be vulnerable to another party" (Mayer et al., 1995; p. 726). Trust is a critical aspect of the transitions to algorithmic HRM (Höddinghaus et al., 2021) and HR professionals play a central role in cultivating and maintaining trust. In the context of algorithmic management, trust is indicated by employees' confidence in the organization's use of digital technologies – particularly algorithm-driven HR systems. Predictors of initial employee trust in algorithmic systems differ from those that are required to maintain trust over time (Cabiddu et al., 2022). Cultivating trust in algorithmic HRM requires a dual strategy.

Initial trust is largely shaped by employees' first interactions with the system: Users are more likely to trust algorithmic systems that require lower cognitive load (Alexander et al., 2018). Three key factors influence initial trust: (1) a user's general propensity to trust, (2) the human-like characteristics of AI (e.g., fairness, transparency, and accountability), and (3) perceived usefulness (Cabiddu et al., 2022). For instance, studies that examine fairness perceptions associated with algorithmic recruitment and selection systems show that solely algorithmic systems are judged to be less fair compared to human-assisted systems (Lavanchy et al., 2023). At the initial algorithmic interaction stage, it is therefore recommended that HR managers:

- prioritise transparency, accountability, and human-like fairness of algorithmic systems;

- proactively communicate the types of employee data being collected, the intended purposes, and the safeguards in place (e.g., opportunities for questioning or appealing algorithmic decisions).

As trust develops over time, focus shifts to maintaining trust by fostering familiarity through repeated, clear interactions with the algorithm.

Trust over time is shaped by (1) social influence, (2) growing familiarity with the system, and (3) the system-like characteristics of the algorithm (e.g., learned usefulness, reliability and ability of the algorithm to perform; Cabiddu et al., 2022). Confirming trust as a social process, it has been shown that prior use of algorithms by others fosters trust building and maintaining process (Alexander et al., 2018). For maintaining trust (and perceived fairness) in algorithmic management, it is essential that employees should be able to track, understand, and predict how algorithms behave. For HR managers, maintaining trust therefore requires:

- Ongoing engagement and responsiveness to employee queries about algorithmic systems
- Sustained transparent communication about algorithmic systems
- Routine performance audits of algorithmic decisions and the data that are used to train algorithms
- Continued employee involvement in shaping algorithmic management systems

Additionally, creating opportunities for peer support and leveraging social influence can further sustain trust in these systems.

Trust is not a static condition but an evolving dynamic that must be deliberately cultivated throughout the lifecycle of algorithmic HRM implementation. Building initial trust requires transparency around data use, clear communication about the system's purpose, and alignment with ethical values such as fairness and accountability. Sustaining trust over time depends on employee familiarity with the system, consistent performance, opportunities for engagement, and meaningful avenues for contesting outcomes. Given the complexity and potential opacity of algorithmic systems, HR professionals must act not only as technical implementers but also as ethical facilitators – ensuring that technology serves human goals, not the reverse. As algorithmic tools continue to transform HR practices, the challenge is not simply to deploy them efficiently, but to do so in a way that strengthens organizational integrity, protects employee dignity, and reinforces mutual trust. We next consider a list of reflective practice questions that may guide HR managers in enabling responsible and trust-building algorithmic HRM systems.

Reflective HR practice for responsible and trust-building algorithmic HRM

Building on this brief review of the existing empirical evidence on algorithmic management systems (e.g., Breidbach, 2024; Cadiddu et al., 2022; Schafer et al., 2022) and their impact on employee experience and perceptions, below we offer a set of reflective questions that may guide HR practitioners when designing and implementing algorithmic HRM strategies.

Strategic alignment of algorithmic decision-making:

- What is my organization's strategy?
- What are my project's objectives?
- Can algorithmic decision-making help achieve organizational objectives? If so, how?
- Who is responsible for preparing AI-related strategies?

Organizational consensus on what 'ethical' and 'responsible' mean:

- What does ethical mean for me?
- Is there a danger that certain employees or groups will be disadvantaged or discriminated against with the use of algorithms?
- Are we aware of our own biases? How can be get better at identifying our own biases?
- Who is responsible if something goes wrong?
- Does our approach to algorithmic management respect autonomy of workers?

Data management:

- What kind of data do we need? What kind of data do we use?
- Are we gathering the correct data, considering the organization's goals?
- Who has access to the dataset and how is access monitored?
- Which laws and regulations apply to data management?
- Who/what team is responsible for handling data ethically?
- Can the HR team explain how algorithms work?

Training the algorithm:

- What is the source of the data that algorithms use? Has it been checked for quality?
- To what extent is our AI training rigorous enough to mitigate any biases?
- Who is missing in the dataset? Is the sample near-enough representation of your workforce?
- What processes do we have in place for auditing algorithms for biases?
- Are the algorithms suitable for the tasks they are set out to achieve?

Transparency of algorithms:

- (How) do we inform workers that their data is used to build algorithms?
- (How) do we inform workers how the algorithms are used in supporting / making HR decisions.
- Is there danger of worker/employee outrage with the way data and algorithms are used?

Evaluating effectiveness:

- What outcomes do we expect from using algorithmic management?
- How do we measure effectiveness of using algorithms in employee management decisions?
- Does a human control/oversee outcome of decisions that are taken by algorithms?

Conclusion

Algorithmic HRM represents a profound transformation in how organizations manage, monitor and engage their workforce. Although algorithmic systems promise efficiency and objectivity, their implementation raise critical concerns related to fairness, employee autonomy and trust. As this paper has demonstrated, algorithmic HRM can decrease workers' sense of agency, reinforce biases, and reduce the richness of human work to quantifiable metrics – unless actively managed with ethical intent.

In this evolving landscape, HR professionals occupy a pivotal role: not just as implementers of digital systems, but as a bridge of fairness, transparency and trust. HR professionals may act as facilitators – bridging the gap between algorithmic decisions and worker response. When algorithmic outputs produce unexpected results (e.g., performance flags, denied promotions, misaligned training suggestions), it is the human layer of HRM that must translate, contextualise, and – when necessary – intervene.

Ultimately, the challenge is not whether we adopt algorithmic systems in HR, but how we do so responsibly. The future of work depends on our ability to harness technological progress without sacrificing human dignity. HR must rise to this challenge – by shaping not just the tools we use, but the kind of workplaces we want to create.

References

Association for Computing Machinery (2017). *Statement on algorithmic transparency and accountability*. US Public Policy Council. https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf

Adams-Prassl, J., Abraha, H., Kelly-Lyth, A., Silberman, M. S., & Rakshita, S. (2023). Regulating algorithmic management: A blueprint. *European Labor Law Journal*, *14*(2), 124–151. https://doi.org/10.1177/20319525231167299

Alexander, V., Blinder, C., & Zak, P. J. (2018). Why trust an algorithm? Performance, cognition, and neurophysiology. *Computers in Human Behavior*, *89*, 279–288. https://doi.org/10.1016/j.chb.2018.07.026

Baiocco, S., Fernandez-Macias, E., Rani, U., & Pesole, A. (2022). The algorithmic management of work and its implications in different contexts. *JRC Working Papers Series on Labour, Education and Technology, 2022*(02). J. R. Centre. https://publications.jrc.ec.europa.eu/repository/handle/JRC129749

Bondarouk, T., & Brewster, C. (2016). Conceptualising the future of HRM and technology research. *The International Journal of Human Resource Management*, *27*(21), 2652–2671. https://doi.org/10.1080/09585192.2016.1232296

Bonini, T., & Treré, E. (2024). *Algorithms of resistance: The everyday fight against platform power*. MIT Press. https://doi.org/10.7551/mitpress/14329.001.0001

Braverman, H. (1998). *Labor and monopoly capital: The degradation of work in the twentieth century*. NYU Press.

Breidbach, C. F. (2024). Responsible algorithmic decision-making. *Organizational Dynamics*, *53*(2), 101031. https://doi.org/10.1016/j.orgdyn.2024.101031

Bucher, E. L., Schou, P. K., & Waldkirch, M. (2021). Pacifying the algorithm – Anticipatory compliance in the face of algorithmic management in the gig economy. *Organization*, *28*(1), 44–67. https://doi.org/10.1177/1350508420961531

Cabiddu, F., Moi, L., Patriotta, G., & Allen, D. G. (2022). Why do users trust algorithms? A review and conceptualization of initial trust and trust over time. *European Management Journal*, *40*(5), 685–706. https://doi.org/10.1016/j.emj.2022.06.001

Cameron, L. D., & Rahman, H. (2022). Expanding the locus of resistance: Understanding the co-constitution of control and resistance in the gig economy. *Organization Science*, *33*(1), 38–58. https://doi.org/10.1287/orsc.2021.1557

Charlier, R., & Kloppenburg, S. (2017). *Artificial Intelligence in HR: A no-brainer*. pwc. https://www.pwc.at/de/publikationen/verschiedenes/artificial-intelligence-in-hr-a-no-brainer.pdf

Chartered Institute of Personnel and Development (2023). *Using AI responsibly in people management*. https://www.cipd.org/uk/views-and-insights/thought-leadership/insight/ai-people-management/

Chartered Institute of Personnel and Development (2024). *How to choose the right technology for your business*. https://www.cipd.org/uk/knowledge/guides/responsible-investment-technology/

Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2022). Examining the impact of algorithmic control on Uber drivers' technostress. *Journal of Management Information Systems*, *39*(2), 426–453. https://doi.org/10.1080/07421222.2022.2063556

Dastin, J. (2022). Amazon scraps secret AI recruiting tool that showed bias against women. In K. Martin (Ed.), *Ethics of data and analytics* (pp. 296–299). Auerbach Publications.

Davenport, T. (2014). How strategists use "big data" to support internal business decisions, discovery and production. *Strategy & Leadership*, *42*(4), 45–50. https://doi.org/10.1108/SL-05-2014-0034

Dube, C. (2025). *What HR needs to know about AI in 2025*. People Management. https://www.peoplemanagement.co.uk/article/1903571/hr-needs-know-ai-2025

Duffy, C., & Dotto, C. (2023). *People are missing out on job opportunities on Facebook because of gender, research suggests*. CNN Business. https://edition.cnn.com/2023/06/12/tech/facebook-job-ads-gender-discrimination-asequals-intl-cmd/index.html

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal*, *30*(1), 114–132. https://doi.org/10.1111/1748-8583.12258

Frey, B. (2020). Platform labor and in/formality: Organization among motorcycle taxi drivers in Bandung, Indonesia. *Anthropology of Work Review*, *41*(1), 36–49. https://doi.org/10.1111/awr.12187

Gandini, A. (2018). Labour process theory and the gig economy. *Human Relations*, *72*(6), 1039–1056. https://doi.org/10.1177/0018726718790002

Gondim, S. M. G., Carneiro, L., Viego, V., Renteria-Perez, E., Cifuentes-Leiton, D., Moscon, D., Ansoleaga, E., & Agullo-Tomas, E. (2024). Effects of flexibility on digital platform-mediated work in five Ibero-American countries. *Social Sciences*, *13*(7), 340. https://doi.org/10.3390/socsci13070340

Grand Review Research (2025). *AI in HR market size & trends*. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-hr-market-report

Hoang, L., Blank, G., & Quan-Haase, A. (2020). The winners and the losers of the platform economy: Who participates? *Information, Communication & Society*, *23*(5), 681–700. https://doi.org/10.1080/1369118X.2020.1720771

Höddinghaus, M., Sondern, D., & Hertel, G. (2021). The automation of leadership functions: Would people trust decision algorithms? *Computers in Human Behavior*, *116*, 106635. https://doi.org/10.1016/j.chb.2020.106635

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, *178*(4), 977–1007. https://doi.org/10.1007/s10551-022-05049-6

Kavakeb, D. (2023). *Facebook accused of gender discrimination, new research finds bias in advertising algorithm*. Global Witness. https://globalwitness.org/en/press-releases/facebook-accused-of-gender-discrimination-new-research-finds-bias-in-advertising-algorithm/

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Lamers, L., Meijerink, J., Jansen, G., & Boon, M. (2022). A capability approach to worker dignity under algorithmic management. *Ethics and Information Technology*, *24*(1), 10. https://doi.org/10.1007/s10676-022-09637-y

Lavanchy, M., Reichert, P., Narayanan, J., & Savani, K. (2023). Applicants' fairness perceptions of algorithm-driven hiring procedures. *Journal of Business Ethics*, *188*(1), 125–150. https://doi.org/10.1007/s10551-022-05320-w

Loveday, S. J. (2024). *HR's role in making sure AI is ethical*. People Management. https://www.peoplemanagement.co.uk/article/1873951/hrs-role-making-sure-ai-ethical

Mayer, R., Davis, J., & Schoorman, F. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.2307/258792

Meijer, A., & Grimmelikhuijsen, S. (2020). Responsible and accountable algorithmization: How to generate citizen trust in governmental usage of algorithms. In M. Schuilenburg & R. Peeters (Eds.), *The algorithmic society* (pp. 53–66). Routledge.

Meijerink, J., Boons, M., Keegan, A., & Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *International Journal of Human Resource Management*, *32*(12), 2545–2562. https://doi.org/10.1080/09585192.2021.1925326

Meijerink, J., & Keegan, A. (2019). Conceptualizing human resource management in the gig economy: Toward a platform ecosystem perspective. *Journal of Managerial Psychology*, *34*(4), 214–232. https://doi.org/10.1108/JMP-07-2018-0277

Möhlmann, M., & Zalmanson, L. (2017). Hands on the wheel: Navigating algorithmic management and Uber drivers' autonomy. *Proceedings of the International Conference on Information Systems (ICIS 2017)*.

Parent-Rocheleau, X., Parker, S. K., Bujold, A., & Gaudet, M. C. (2024). Creation of the algorithmic management questionnaire: A six-phase scale development process. *Human Resource Management*, *63*(1), 25–44. https://doi.org/10.1002/hrm.22185

Popan, C. (2024). Embodied precariat and digital control in the "gig economy": The mobile labor of food delivery workers. *Journal of Urban Technology*, *31*(1), 109–128. https://doi.org/10.1080/10630732.2021.2001714

Prassl, J., & Risak, M. (2017). The legal protection of crowdworkers: Four avenues for workers' rights in the virtual realm. In P. Meil & V. Kirov (Eds.), *Policy implications of virtual work* (pp. 273–295). Springer. https://doi.org/10.1007/978-3-319-52057-5_11

Rubel, M. R. B., Kee, D. M. H., Rimi, N. N., & Yusoff, Y. M. (2017). Adapting technology: Effect of high-involvement HRM and organisational trust. *Behaviour & Information Technology*, *36*(3), 281–293. https://doi.org/10.1080/0144929X.2016.1222552

Scholz, T. M. (2019). Big data and human resource management. In J. S. Pedersen & A. Wilkinson (Eds.), *Big data: Promise, application and pitfalls* (pp. 69-89). Edward Elgar. https://doi.org/10.4337/9781788112352.00008

Soliman, I. (2025). *Majority of HR now willing to use AI, study reveals*. People Management. https://www.peoplemanagement.co.uk/article/1909620/majority-hr-willing-use-ai-study-reveals

Weiskopf, R., & Hansen, H. K. (2023). Algorithmic governmentality and the space of ethics: Examples from 'People Analytics'. *Human Relations*, *76*(3), 483–506. https://doi.org/10.1177/00187267221075346

Wesche, J. S., & Handke, L. (2023). Digitisation and automation in training and development: A meta-review of new opportunities and challenges. *Personnel Review*, *53*(3), 771–790. https://doi.org/10.1108/PR-09-2022-0660